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RE-EXAMINING STOCK MARKET INTEGRATION AMONG BRICS COUNTRIES

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Abstract

The main goal of this paper is to contribute to the international investment decision making process among the BRICS countries and to the development or changes of policies in response to the dynamics in these countries. The background is important for international investors seeking diversification benefits abroad and for policy makers reacting to the developments in the aforementioned economies. Thus, the context of this paper is directed to the examination of the stock market interaction among the BRICS countries. The objective of this research paper is to analyze the existence of the short-term linkages and long-term cointegration among the BRICS markets. Augmented Dicker-Fuller (ADF) and Philips-Perron tests (PP) are used to analyze stationarity among the selected variables. The research applies the correlation test on the stock markets returns to investigate the degree of freedom existing among the markets. The long run and the short run are also investigated using Johansen cointegration test while the Pairwise Granger Causality and the Wald tests are applied to assess the direction of the causality between the stock market indices. The study also extends the investigation by employing the impulse response function and variance decomposition to evaluate the reaction of each stock to a shock from other stock indices. The quarterly data consisted of fifteen years from 2000 to 2015 and are exclusively composed of stock market index of selected countries. One of the key findings of the research is that the Chinese stock markets are mostly independent from other BRICS markets, implying diversification benefits for the international investors both in the short and the long run. Another important finding is that the BRICS stock markets are not cointegrated in the long run, thus, being a favorable destination for the long-term investments.

Keywords: BRICS Stock Markets, Integration, ADF and PP Tests, JJ Cointegration Test, Granger Causality Test, VAR, Impulse Response Function, Variance Decomposition Analysis

1. Introduction

Nowadays the integration of the global economic and financial systems is increasing due to the rapid growth of the international trade in commodities, services, as well as financial assets. While the economic integration of different countries is increasing based on the high and growing volumes of the imported and exported goods, the level and trend of the international financial integration is increasing even more with the relaxation of capital controls among the economies. The existence of cointegration among the stock markets of different countries suggests lower diversification benefits and inefficiency in the markets. When markets are not cointegrated, the investors act to benefit from the international diversification to reduce the country specific risk (unsystematic risk) and to increase the risk-reward ratio. But, when the markets are cointegrated, those benefits dry away. Thus, the investors seek to find the best risk-return portfolios in the scope of the growing international financial integration, which significantly influences the ability of governments to carry out independent economic policy.

Currently, with growing trends of globalization, the investors have become more active in foreign financial markets, which imply that the global financial integration issue has gained high importance among them. Taking into consideration the fact, that the level of integration has also its macroeconomic and monetary implications, it is also subject for “great” concern among the policy makers with the necessity to react to the ever-changing global dynamics. Thus, the aforementioned statements explain the huge interest of academic researchers in the level and trend of the financial cointegration among different countries.

The recent financial crisis in America, as well as in most countries of Europe, made the international investors to seek for other markets as “safe” destination of their investment funds. One of the destinations has come to be the emerging markets with the BRICS markets having dominant role here.

Most of the countries of BRICS are the largest and most integrated economies in their corresponding regions. Thus, they have more significant role in the world economic dynamics compared to the other emerging markets. This means, that simultaneous economic slowdown in these countries will influence essentially the economic performance of the other countries and the overall global economy. So, the short term linkages and the long-term integration among the mentioned markets play vital role among the investors, policy makers, as well as the researchers. Thus, the BRICS stock markets are selected for the current research analysis, taking into consideration the fact that the stock markets bear the economic, as well as other, for example political developments of their respective countries.

This study aims to find out the short term stock market interaction and the long term cointegration level of the BRICS countries, the causal relationships, as well as the dynamic linkages between them. For this purpose, the previous studies are thoroughly analyzed and econometric techniques are applied. The research is carried out through graphical representations, descriptive statistics, correlation tests, ADF and PP tests, Johansen and Juselius cointegration tests, as well as Granger causality analysis. The study goes further by applying the VAR model, Impulse response and the Variance Decomposition techniques. Quarterly data is taken for the period of 2000 till 2015 years from the Bloomberg database.

The research paper is organized as follows: theoretical framework and hypothesis development, BRICS economies overview, literature review, research design and methodology presentation, analysis of the results and the conclusion driven from the implemented analyses. This paper provides new insights in the scope of the stock market integration.

2. Theoretical Framework and Hypothesis Development

The modern portfolio theory implies that when the markets are fully integrated, the investors are indifferent in which market to invest their funds, as they are compensated similarly for taking the systematic risk. Thus, the only factor determining the asset prices is the systemic risk related to the global market. But for a fully segmented market, the deterministic factor of the asset pricing is the domestic market systemic risk. With the current trends of globalization of the world markets, the systemic risk must incorporate the risks related to the other markets, which becomes the deterministic factor of the CAPM. The efficient market hypothesis (EMH) is the proposition that the current stock prices fully reflect all the relevant information, including the information regarding the systematic risk. From the global perspective, the unsystematic risk is the risk related to separate country’s stock market and can be reduced through diversification, whereas the systematic risk is inherent to the entire global market. The CAPM uses the non-diversifiable or systemic risk for pricing the assets. In this scope, the international investors can get diversification benefits through investing in different countries’ stock markets and are compensated for taking the systemic risk, which is included in the information incorporated in the stock prices. Thus, the CAPM is taken as the theoretical framework for this research. The objective is to investigate the existing interrelationships among the BRICS stock markets and the possibility of the diversification gains in those markets. The study is carried out through using some hypothesis tests for evaluating the short term linkages, and well as the long term cointegration of the stock markets.

3. BRICS Economies Overview

The global economy showed declining trends in 2015 recording 2.4% real GDP growth compared to 2.6% of 2014, which is mainly due to the continued economic decline in emerging and developing economies (World Bank Group, 2016). It is estimated that BRICS countries contributed almost 40% to the world economic growth during 2010-2014. Currently, BRICS markets compose nearly two-thirds of the emerging economies. Thus, the simultaneous economic slowdown in these countries will surely have its essential influence on the economic performance of the other countries. For instance, according to the estimates of the World Bank Group (2016), 1% decline in BRICS economies will result in the decrease in economic growth by 0.8% in other emerging markets and 0.4% in the world economy during a period of two years. As most of the countries in BRICS are the largest and most integrated economies in their corresponding regions, they tend to have greater impact compared to other major emerging markets.

It is worth mentioning that China is the largest country among the emerging markets and composes two-thirds of the size of the other emerging economies combined. China is also twice the size of the other BRICS markets combined. Table 1 illustrates the real GDP actual and forecasted growth rates for the years of 2013-2018.

Table 1. The Real GDP Actual and Forecasted Growth Rates

	2013 actual	2014 actual	2015 estimate	2016 forecast	2017 forecast	2018 forecast
World	2.4%	2.6%	2.4%	2.9%	3.1%	3.1%
Emerging Markets	4.9%	4.5%	3.7%	4.2%	4.8%	4.9%
BRICS	5.7%	5.1%	3.9%	4.6%	5.3%	5.4%
Brazil	3.0%	0.1%	-3.7%	-2.5%	1.4%	1.5%
Russia	1.3%	0.6%	-3.8%	-0.7%	1.3%	1.5%
India	6.9%	7.3%	7.3%	7.8%	7.9%	7.9%
China	7.7%	7.3%	6.9%	6.7%	6.5%	6.5%
South Africa	2.2%	1.5%	1.3%	1.4%	1.6%	1.6%

Source: World Bank Group (2016)

The economic growth recorded declining trend in emerging markets from the 7.6% in 2010 to 3.7% in 2015. It is forecasted slight increase in GDP for the emerging markets for the next three years, which is still lower compared to that of 2010. Referring to BRICS countries, the economic growth decreased from 9% in 2010 to 3.9% in 2015. The decline was recorded in almost all BRICS countries, excluding India. Slight declining trends are seen in China and South Africa in 2014 and 2015, and thorough recessions are observed in Russia since 2014 and Brazil since 2015. The economic slowdown in most BRICS countries was the result of both external and internal factors. The unfavorable external environment; such as weak global trade, steady decline in commodity prices and tightening global financial conditions, are the key source of the economic decline between 2010 till the first quarter of 2014, after which the domestic factors; such as decline in productivity and uncertainty in policy, gain the basic role. Those factors are estimated to continue having their adverse impact on the BRICS economies, although it is anticipated that the recessions in Russia and Brazil will start to weaken since 2016.

4. Literature Review

In literature, the integration of international financial markets falls into two categories: direct and indirect (Kearney and Lucey, 2004). The direct measure refers to the law of one price; i.e. the existence and the level of equal rates of returns of the financial assets of different countries having identical risk and maturity, which will be the result of the unrestricted capital flows among those economies. The indirect measure refers to the level of the completeness of the international capital markets and to the degree the local domestic investment is financed through the international sources. Thus, the high degree of international financial integration will imply low levels of diversification benefits.

The current research analyzes the integration among the BRICS stock markets, thus, similar previous studies are briefly considered in this context. Korajczyk (1996) investigated the integration of developed and emerging markets and revealed that the market segmentation is higher for the emerging markets compared to the developed countries, which is explained by the existing barriers to capital flows into or out of the emerging economies. Thus, the stock markets of developed countries are more integrated than those of the emerging markets. It is worth mentioning that the level of integration tends to increase over time resulting in the decrease in market segmentation.

Mukhopadhyay (2009) analyzed the financial market integration and came to the following conclusions: market integration is more apparent among markets at comparable development stage; market integration is mostly lead by the developed markets; and the emerging markets are more vulnerable to the consequences of distress than the developed ones.

Shachmurove (2006) analyzed the dynamic linkages among the US stock exchanges and the four "Emerging Tigers of the Twenty First Century" - BRICs. The daily observations were used for the period of May 1995 till October 2005, for a total of 2641 observations, as well as VAR model, Impulse Response, Variance Decomposition were applied for the analysis. The study illustrated that the Brazilian stock markets are significantly influenced by the other countries' stock markets. Russian stock markets are also affected by the other markets but only to a lesser extent. What refers to China and India, they are less impacted by the other markets. The study also revealed that the Chinese stock markets are mostly independent from the other markets' influence including the US stock market, and thus, can serve as a source of diversification for the mentioned countries.

Tirkkonen (2008) analyzed the integration of Russian financial markets both for the in-country and cross-country markets. The study applied the VAR model and Johansen cointegration test using the daily data for the period of 1st January 2003 till 28th December 2007. The results indicated that the Russian stock markets are segmented and do not have short or long term relationship. Thus, one may gain benefits from the diversification.

Koźluk (2008) thoroughly studied the stock markets of Russia and China as part of a deeper analysis of 135 stock indices of 75 countries. The results indicated that Russian stock market essentially increased its integration level with global stock markets, as usually emerging markets behave. But what refers to China, the study revealed that its A-share and B-share markets behaved independently from the global market dynamics showing some increase in interrelation with the regional markets. The study also indicated an increasing trend in global integration of the stock markets during the past years leading to decreasing influence of the regional forces, which results in reduced benefits from the cross-country diversification and hedging strategies.

Bhar and Nikolova (2009) conducted cointegration analysis between BRIC countries, their respective regions and the world, using the weekly data for the period January 1995 to October 2006. The studies indicated that India has the most regionally and globally integrated stock market among the BRIC countries. After come the stock markets of Brazil, Russia and lastly China. The analysis, thus, implied that investors can gain diversification opportunities in China.

Chittedi (2010) used Granger causality, Johansen cointegration and ECM for analyzing the integration of the stock markets among the BRIC countries, as well as their integration with the stock markets of US, UK and Japan. The data were composed from the daily stock market indices for the period of January 1998 till August 2009. As a result, the study found an evidence of cointegration between BRIC and the developed countries. The analysis also concludes that US and Japan markets influence Indian market, but the stock markets of UK, Brazil, Russia and China do not influence Indian market.

Awokuse *et al.* (2009) examined the interrelation among the stock markets of the US, UK, Japan and ten Asian stock markets. The results suggested time varying cointegration relationships among the mentioned markets. Moreover, the analysis found that the US and Japan affect strongly the emerging markets.

An *et al.* (2010) studied the US and BRIC stock markets through analyzing the weekly and monthly index returns during October 13, 1995-October 13, 2009. The study found some evidence of cointegration between the US and China, and no evidence of integration between the US and other markets. Thus, the analysis concluded that international investors can gain from the diversification opportunities in the mentioned emerging countries' stock markets excluding China.

Chow *et al.* (2011) ran time-varying regression for analyzing the interlinkages between the Shanghai and New York stock markets. The study found growing trend in the degree of integration of the Chinese and word stock markets with some interruptions during the recent financial crisis.

Gupta (2011) examined the relationship among emerging countries, with special stress on the BRIC countries, during the financial turmoil. The daily closing indices are used for the time span from January 2008 till November 2011. Granger Causality test was applied in order to assess the causal relationship among the BRIC indices. The results of the study illustrated that economies of India, Russia and China granger cause the Brazilian economy, but the opposite is not true. Russia does not granger cause the Indian economy, but Indian economy granger causes the Russian economy. Chinese economy has bidirectional causality with India and Russia, meaning that Chinese economy is highly interdependent on Indian and Russian economies.

Sharma *et al*. (2013) analyzed the relationships between the BRICS stock market indices. Regression analysis, Granger causality model, VAR model, Variance Decomposition Analysis and Impulse Response are applied for studying the interconnections of the emerging market indices. The analysis revealed slight interconnections among the BRICS indices, implying diversification opportunities for global investors. Furthermore, the study implied that the stock markets bear the impact of the domestic macro-economic factors.

Dasgupta (2014) conducted analysis on integration of the Indian stock markets with BRIC markets. The data used composed of the daily closing values of the BRIC stock market indices for the period of 1st January 2003 to 31st December 2012. The study used cointegration tests, Granger causality tests for estimating the short and long term relationships among the selected indices, as well as VAR model, Impulse response function and Variance decomposition analyses are also implied. The analysis revealed one cointegration indicating long-run relationships, as well as short-run bidirectional Granger relationships between the Indian and Brazilian stock markets. Moreover, the Chinese stock market Granger causes the Brazilian stock market and the latter impacts the Russian stock market. The study also illustrated that the Indian stock market has strong impact on Brazilian and Russian stock markets, and thus, the Indian stock market has the dominance among the BRIC countries.

Naidu *et al.* (2014) investigated the cointegration in capital markets of BRICS countries. The study found no integration among the BRIC markets when using the data from 1997-2014. However, Johansen cointegration test found one cointegrating vector when analyzing the BRICS stock markets for the period of 2009-2014, which implies the existence of the long-term equilibrium relationship among these indices, and, thus, no diversification gains for the investors in these markets. It is also worth to mention that no pairwise causal effects are found according to the results of the Granger causality tests. Interesting evidence was found during the analysis, indicating the negative correlation between China and India stock market indices implying the independent nature of these markets.

Nashier (2015) employed the correlation and Johansen cointegration tests to assess the integration level between the BRICS stock markets and the stock markets of US and UK using the data span from 1st January 2004 till 31st of December 2013 with total of 2201 observations of daily closing prices. The study concluded that there exist short and long term integrations between the mentioned markets implying low level of diversification.

To summarize the above-mentioned literature survey on stock market integration, it is evident that the results and findings contradict each other. The variation of the results is mainly the result of variable selection, the applied research methodology, the selected countries subject for the analysis, as well as the period of study and its length. Thus, a single general conclusion cannot be driven from the literature survey.

The current research aims to fill the gap that exists in the aforementioned studies. Particularly, this study is unique and innovative, as it is the first to investigate market interdependencies using the BRICS recent stock prices. In this scope, the research can compete with three of the above-mentioned studies. For example, Sharma *et al.* (2013) have conducted similar analysis with the BRICS stock market indices by using the daily closing prices from 2005-2010, which does not capture the recent dynamics. Besides, the results of the Impulse Response and the Variance Decomposition analysis do not provide considerable long-term implications by using data on daily intervals. Naidu *et al.* (2014) also analyzed the BRICS countries using monthly observations for 1997-2014. The data is used in local currencies in exact values, as well as in logarithmic values. The local currency values cannot be compared and show inflated returns, while using the logarithmic values means transforming the model, which may cause a low quality model to appear well-behaved. Moreover, the study limits its analysis through using the Granger causality and the Johansen cointegration tests. Nashier (2015) has also analyzed the BRICS stock markets using the daily prices for the period of 2004-2013. This study also does not capture the recent data trends. The study also limits in using the correlation test and the Johansen cointegration test. As different countries are spread in different time zones, using the daily data in the analysis will have some inaccuracies. Besides the cointegration is a long-term phenomenon, and thus long-term spans of data are required than high frequency data. Thus, this research covers the aforementioned gaps existing in the previous studies by using the up-to date data on quarterly intervals, as well as applying complete econometric techniques and different models.

5. Research Design and Methodology

5.1. Research Design

Saunders *et al.* (2009) provide a six-step guide for conducting and designing a research: Philosophy, Approach, Strategy, Choice, Time horizon, Technique and procedure. The research reflects the philosophy of positivism, as it deals with observable social reality. The quantitative data are collected from the social environment bearing the influence of people, namely investors and governments, on it, and the research is undertaken in a value-free way with no influence on the substance of the data.

This research aims to analyze the causal relationship of the stock market indices both in the short and the long run through testing some hypothesis on the existing theory based on the quantitative data analysis, and thus, follows the deductive approach of theory development. The case study strategy is employed for doing this research, as it is directed to explore the linkages of the stock markets and involves the investigation of the indices within their real life context. This research adopts the Quantitative approach to data analysis through using numerical data series. The time horizon is characterized as longitudinal, as the research applies quarterly data series for fifteen years from 2000 to 2015 with total of 62 observations, and studies their dynamics and developments. The following stock market indices are selected for the analysis and are presented in Table 2 below:

Table 2. Indices of BRICS countries

Country	Stock Market Index	Abbreviation
Brazil	Index of the Bolsa Oficial de Valores de São Paula	IBOV
Russia	Russian Trading System Index	RTS
India	NIFTY 50	NIFTY
China	Shanghai Stock Exchange Composite of China	SHCOMP
South Africa	JSE Africa All Shares Index	JALSH

The data are collected from the Bloomberg database (www.bloomberg.com) and compose from quarterly returns of the stock market indices expressed in GBP for a period of fifteen years from 2000 to 2015. The data are used both in their actual values, and in logarithmic transformation. The Eviews software package is used for carrying out the analysis.

5.2. Research Methodology

As we are dealing with time series data, the first thing to consider is normality and the level of stationarity. The Jarque-Bera test (Gujarati, 2003) is used here for testing the hypothesis of normal distribution. The test computes the skewness and kurtosis and compares them with those of the normal distribution. The Augmented Dicker-Fuller (ADF) (Dickey and Fuller, 1979; 1981) and Philips et al (1988) unit root tests are applied for testing the stationarity of the series. Eviews carries the ADF test by using the following equation:

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \beta_1 \Delta y_{t-1} + \beta_2 \Delta y_{t-2} + \cdots + \beta_p \Delta y_{t-p} + \vartheta_t, \tag{1}$$

where
α- coefficient of y_{t-1} to be estimated,
x_t – optional exogenous regressor consisting of a constant, or a constant and trend,
δ – coefficient of x_t to be estimated,
β_t- coefficients to be estimated,
p - lag order of AR(p) process
ϑ_t- white noise.

The null hypothesis is H_0: α=0, against the alternative of H_1: α<0. The null of a unit root existence is rejected in case α is negative and significantly different from zero, implying that the series are stationary – I (0). The null is rejected in case t-statistic value is lower than its critical value and the p-value is less than say 5% (for the current analysis 5% significance level is taken into consideration). If the null is not rejected, meaning that the series are non-stationary, then they must be differenced to become stationary and tested again.

When performing the ADF test, there is an issue whether to enter the exogenous variable x_t in the model, i.e. should the regression include intercept, or intercept with trend or neither of them. A regression with intercept and trend is a more general case while including irrelevant regressors in the model will decrease the power of the test to reject the null hypothesis of a unit root. For avoiding spurious results, we have run the ADF tests with all the three aforementioned cases.

The existence of the unit roots is also tested through the PP tests. The PP method considers the following equation (non-augmented DF test equation):

$$\Delta y_t = \alpha y_{t-1} + x_t'\delta + \epsilon_t \tag{2}$$

Here again, Eviews allows to choose a regression with intercept, intercept with linear trend or neither. Like the ADF test, we have run the PP test with all the mentioned cases. Correlation test: Going further, the correlation test is used for evaluating the level and the direction of the linear relationship between the selected stock market indices. The closer the correlation coefficient to 1 in its absolute value, the higher is the level of the relationship. The sign of the coefficient shows the direction of the association. It is worth mentioning that correlation alone cannot be used for making conclusions, as the correlation coefficients are upward biased in case the series are heteroskedastic. Besides, correlation tests are used for short term implications. Moreover, correlation does not necessarily imply causation. Thus, Johansen's cointegration test is applied for detection of the long-term relationship among the stock market indices, as well as Granger causality test is used for estimating the short-term causation between the variables.

Granger Causality Test: X_t granger causes Y_t, if it contains past information that helps to predict Y_t, and if Y_t cannot be better explained by its past values (Granger, 1969). The simple bivariate casual model consists of the following pair of regressions:

$$X_t = \sum_{i=1}^{m} a_i X_{t-i} + \sum_{i=1}^{m} b_i Y_{t-i} + \varepsilon_t, \quad (3)$$

$$Y_t = \sum_{i=1}^{m} c_i X_{t-i} + \sum_{i=1}^{m} d_i Y_{t-i} + \vartheta_t, \quad (4)$$

where

X_t, Y_t – stationary time series with zero means,
ε_t, ϑ_t – uncorrelated white noise series.

For X_t to cause Y_t c_i should not be equal to zero, and for Y_t to cause X_t b_i should not be equal to zero. Thus, we test the null hypothesis of $H_0: b_i = c_i = 0$. In case both coefficients are significant, we have feedback relationship between the variables. Eviews runs the Granger causality test illustrating the F statistic and its p-value. Here, again we take the 5% significance level for rejecting the null hypothesis.

Johansen and Juselius Cointegration tests: As the stock market indices are integrated of the same order I (1), the Johansen and Juselius tests are run for estimating the cointegration or the long-run relationship among them (Johansen and Juselius, 1990). The Johansen and Juselius test uses the following regression:

$$y_t = A_1 y_{t-1} + \cdots + A_p y_{t-p} + B x_t + \varepsilon_t, \quad (5)$$

where
y_t – non-stationary I (1) variables,
x_t – deterministic variables
ε_t- innovations
A, B – coefficients to be estimated.

The above-mentioned equation can be transformed to the following form:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + B x_t + \varepsilon_t, \quad (6)$$

where: $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$

If the rank of the matrix Π r < k, implies that there exists k x r matrices with rank r (denote them α and β), such that the following conditions are met: Π=αβ' and β'y_t is stationary I(0), although y_t is not-stationary, where r is the number of the cointegrating vectors (cointegrating relations). Thus, Π=αβ' or the existence of r cointegrating vectors hypothesis is considered.

For estimating the number of the cointegrating vectors the Trace and the Maximum Eigenvalue Tests are implied. The Trace test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of k cointegrating vectors. The maximum eigenvalue test tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r+1 cointegrating vectors. The null hypothesis is rejected if the test statistic is greater than its critical value or the p-value is less than 5%. In case when conflict between the results of the Trace and Maximum Eigen value tests exists, the former is applied (Johansen and Juselius, 1990).

In some cases, the individual unit root tests will show that some of the series are integrated, but the cointegration test will indicate that the $\prod$ matrix has full rank ($r = k$). This apparent contradiction may be the result of low power of the cointegration tests, stemming perhaps from a small sample size or serving as an indication of specification error.

VAR Model: The model type (VAR or VECM) selection decision is based on the result of the Johansen and Juselius cointegration tests. As both the Trace and Maximum Eigenvalue tests indicate no cointegration at 5% level, the VAR model is used for further analysis. VAR model regresses each stock market index to the lagged values of all the BRICS indices. Lag length selection has an essential role in VAR estimation. There are several lag selection criteria, from which the Akaike information criterion is employed in this paper.

VAR Granger Causality/Block Exogeneity Wald Tests: One of the objectives of VAR analysis is to assess the casual relationships among the BRICS stock market indices, which is estimated through the Granger causality tests. Thus, VAR Granger Causality/Block Exogeneity Wald Tests are applied to examine the causal relationship among these indices. Under this system, an endogenous variable can be treated as exogenous. The test uses the chi-square (Wald) statistics for testing the joint significance of each of other lagged endogenous variables, as well as the joint significance of “all” other lagged endogenous variables for every equation of the model.

Impulse Response and Variance Decomposition: Going further the impulse response function is applied for estimating the impact of the one-time one standard deviation shock to one of the innovations on the stock market index current and future values. The shock to one of the indices directly influences that same variable, as well as is spread to the other indices of the BRICS because of the dynamic nature of VAR model. In this context, as the error terms or the innovations are generally correlated and, thus, share some common factors, usually transformation is applied to make them uncorrelated. This means that the ordering of the variables has an important implication in the analysis, and Cholesky ordering is applied in the scope of this research paper. Extending the analysis further, variance decomposition is applied for estimating the relative importance of each random innovation to the variation of the indices.

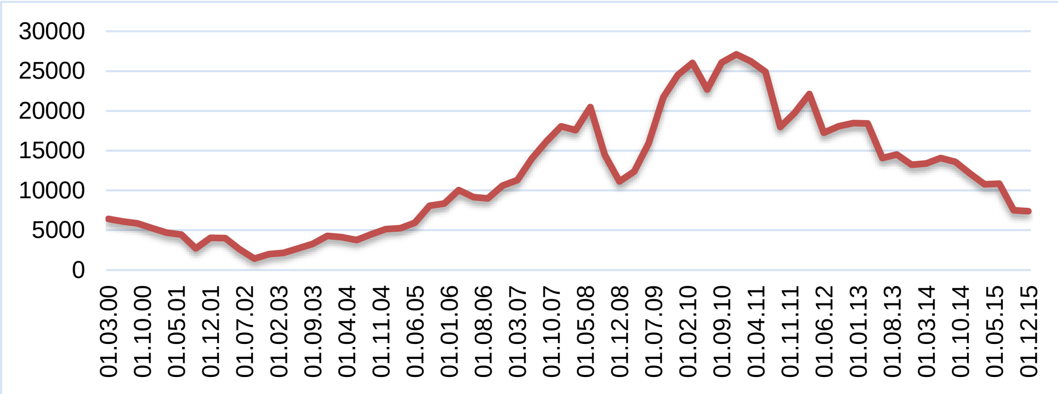
6. Results

For the starting point, it is worth to mention that two models are run with the actual and log values, and the results do not differ significantly. Thus, the model with the actual stock market values is taken for the analysis, as transformation of the model may cause a low quality model to appear well-behaved.

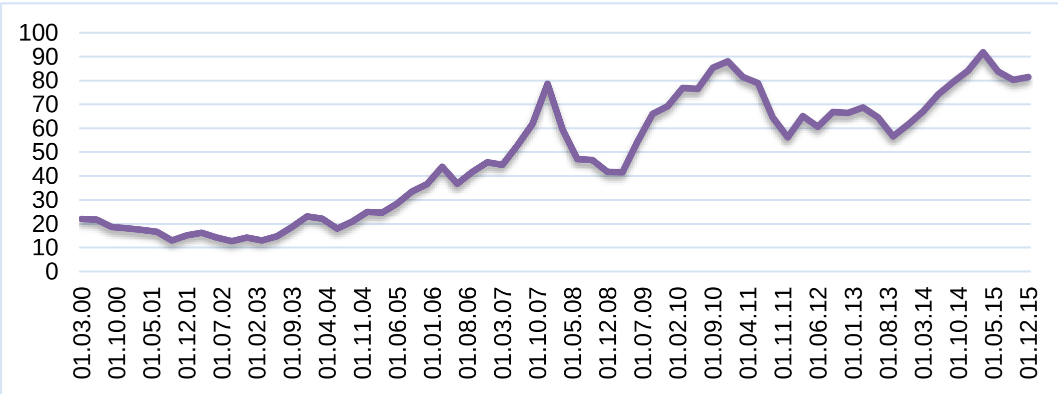
6.1. Index Dynamics and Descriptive Statistics

Figure 1 presents the quarterly dynamic of the BRICS stock indices during 2000-2015. For comparison purposes, all the index values are calculated in GBP. It is visually seen that the volatility of stock indices has increased starting from the end of 2006. Most indices have their peak at the end of 2007 or the first half of 2008, following sharp drop at the end of 2008. IBOV, NIFTY and JALSH have another peak at the end of 2010 and RTS at the end of the first quarter of 2011. IBOV and RTS showed declining trend during 2011-2015. It is worth to mention here that the economies of Russia and Brazil have stepped into recession starting from 2014 and 2015 correspondingly. NIFTY and SHCOMP have demonstrated some decreasing trend with lower values for short and long periods respectively recording another peak at the end of the first and second quarters of 2015 correspondingly. Regarding JALSH, there can be seen some steadiness and little volatility starting from the beginning of 2012 till the first half of 2015 with increasing declining trend recorded during the second half of 2015. Thus, from the graphical representation of the stock indices, we can see that there is some level of correlation among them.

Brazil: Index of the Bolsa Oficial de Valores de São Paula (IBOV)



India: NIFTY 50 (NIFTY)



Russia: Russian Trading System Index (RTS)

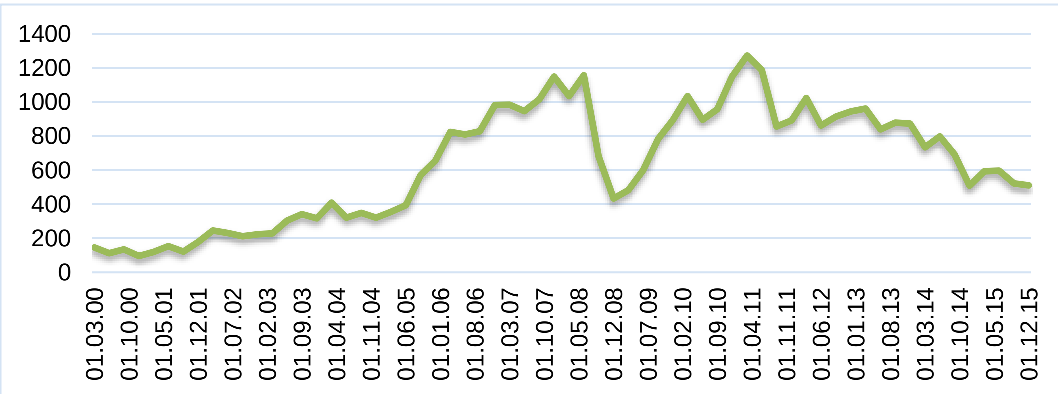
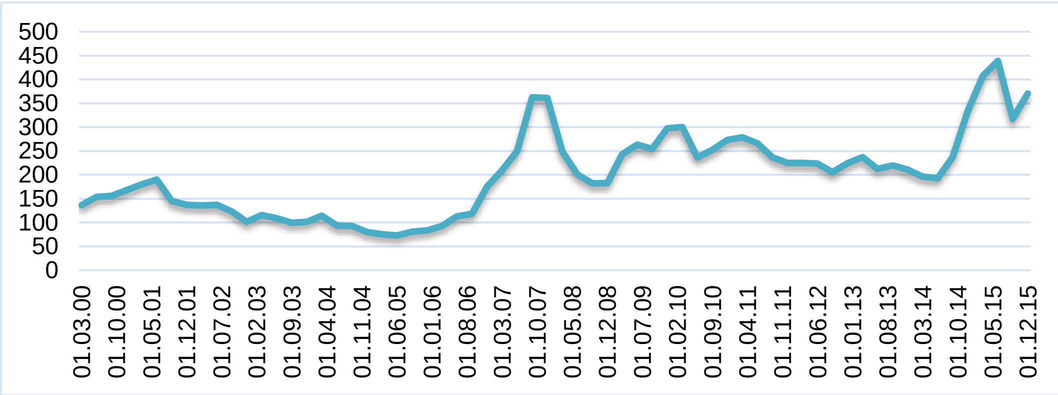


Figure 1. BRICS Indices Dynamic 2000-2015

China: Shanghai Stock Exchange Composite of China (SHCOMP)



South Africa: JSE Africa All Shares Index (JALSH)

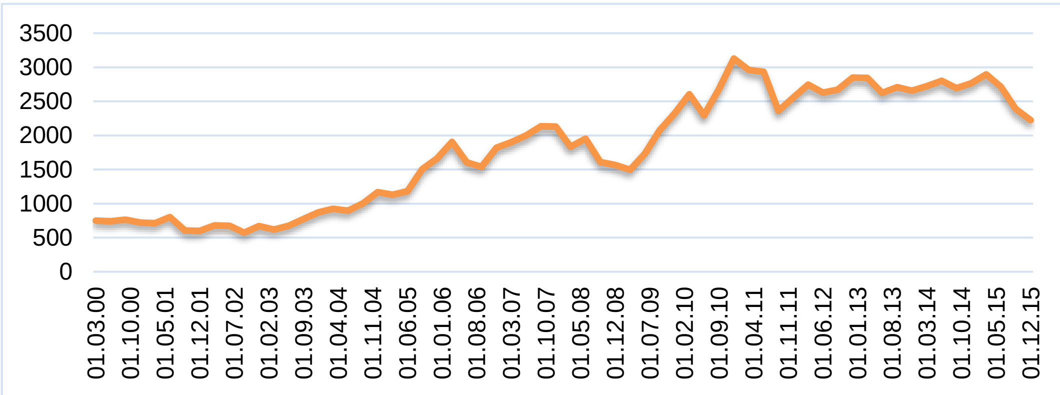


Figure 1 (continued)

Table 3 below presents the correlation ratios of the selected indices. As we see, all indices are positively correlated. The highest correlation ratio is observed between NIFTY and JALSH. Lower correlation levels are observed between IBOV and SHCOMP, as well as RTS and SHCOMP.

Table 3. Correlation of BRICS Stock Indices

	IBOV	RTS	NIFTY	SHCOMP	JALSH
IBOV	1	0.87	0.86	0.66	0.85
RTS	0.87	1	0.81	0.55	0.85
NIFTY	0.86	0.81	1	0.81	0.96
SHCOMP	0.66	0.55	0.81	1	0.70
JALSH	0.85	0.85	0.96	0.70	1

Going further, Table 4 presents the descriptive statistics of BRICS stock indices for the selected period. The standard deviations imply the volatile nature of the stock markets, as is seen from Figure 1. SHCOMP and IBOV have the highest skewness among the selected variables. They have slight positive skewness, which means that the distribution has some long right tail. Regarding the kurtosis, all the indices have a value equal or close to two, except for the SHCOMP, meaning that their distribution is slightly flat (platykurtic) relative to the normal distribution. This implies low probability of the extreme values, since the outlier is less likely to fall within a platykurtic distribution's short tails. SHCOMP has a kurtosis of three, which complies with that of the normal distribution. The Jarque-Bera test measures the compliance of the skewness and the kurtosis to those of the normal distribution. Thus, as we see from the Table 4, the Jarque-Bera statistic value and its probability state that we fail to reject the null hypothesis of a normal distribution at 5% level, but for the NIFTY and JALSH, we will reject the null at 10% level.

Table 4. Descriptive Statistics

	IBOV	RTS	NIFTY	SHCOMP	JALSH
Mean	12,023	639	47	195	1,776
Median	11,230	687	46	195	1,827
Maximum	27,098	1,273	92	439	3,128
Minimum	1,438	96	13	73	572
Std. Dev.	7,431	343	25	84	842
Skewness	0.39	(0.09)	0.08	0.66	(0.05)
Kurtosis	2.05	1.69	1.62	3.18	1.51
Jarque-Bera	3.94	4.55	5.00	4.55	5.79
Probability	0.14	0.10	0.08	0.10	0.06
Sum	745,427	39,613	2,909	12,069	110,119
Sum Sq. Dev.	3,370,000,000	7,180,325	37,760	435,528	43,217,192
Observations	62	62	62	62	62

Next, the ADF and PP test are applied for assessing the level of stationarity of the data. The results are summarized in tables 5.1 and 5.2. The null hypothesis is that the series has a unit root, i.e. it is not stationary. The results of the unit root tests indicate that all the indices are not stationary at level, and that the stationarity is gained after the first difference. Thus, the series are integrated of order one – I (1).

Table 5.1. Augmented Dickey Fuller Test Results

	IBOV			RTS			NIFTY			SHCOMP			JALSH		
	ADF Statistics	Test Critical Value@5%	P-value	ADF Statistics	Test Critical Value@5%	P-value	ADF Statistics	Test Critical Value@5%	P-value	ADF Statistics	Test Critical Value@5%	P-value	ADF Statistics	Test Critical Value@5%	P-value
Intercept	(6.88)	(2.91)	-	(6.96)	(2.91)	-	(6.35)	(2.91)	-	(4.56)	(2.91)	0.00	(7.85)	(2.91)	-
Trend and Intercept	(6.89)	(3.49)	-	(7.03)	(3.49)	-	(6.29)	(3.49)	-	(4.67)	(3.49)	0.00	(7.78)	(3.49)	-
None	(8.88)	(1.95)	-	(6.99)	(1.95)	-	(6.27)	(1.95)	-	(4.50)	(1.95)	-	(7.67)	(1.95)	-
Stationarity Level		I(1)			I(1)			I(1)			I(1)			I(1)	

Table 5.2. Phillips_Perron Test Results

	IBOV			RTS			NIFTY			SHCOMP			JALSH		
	PP Statistics	Test Critical Value@5%	P-value	PP Statistics	Test Critical Value@5%	P-value	PP Statistics	Test Critical Value@5%	P-value	PP Statistics	Test Critical Value@5%	P-value	PP Statistics	Test Critical Value@5%	P-value
Intercept	(6.86)	(2.91)	-	(3.37)	(2.91)	-	(6.35)	(2.91)	-	(4.92)	(2.91)	0.00	(7.87)	(2.91)	-
Trend and Intercept	(6.86)	(3.49)	-	(7.02)	(3.49)	-	(6.29)	(3.49)	-	(5.00)	(3.49)	0.00	(7.79)	(3.49)	-
None	(6.92)	(1.95)	-	(6.96)	(1.95)	-	(6.27)	(1.95)	-	(5.03)	(1.95)	-	(7.67)	(1.95)	-
Stationarity Level		I(1)			I(1)			I(1)			I(1)			I(1)	

The study then uses VAR model and Granger causality in order to find short run linkages and casual relationships between the BRICS indices, as well as Johansen cointegration test is applied for checking the existence of the long run association among the index values. Table 6 below presents the lag length selection criteria need to run the VECM model.

Table 6. Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1622.26	NA	1.19E+19	58.11647	58.29730*	58.18658*
1	-1593.78	50.85302	1.06E+19	57.99227	59.07727	58.41292
2	-1558.5	56.70615*	7.50e+18*	57.62499*	59.61417	58.39619
3	-1539.54	27.08489	9.84E+18	57.84072	60.73408	58.96247
4	-1517.51	27.53982	1.22E+19	57.94673	61.74426	59.41902
5	-1491.05	28.34682	1.41E+19	57.89469	62.5964	59.71753

Note: * indicates lag order selected by the criterion.

The further analyses are done by selecting the lag length of two, as indicated by the AIC, as well as FPE and LR criteria. Johansen-Juselius Tests are implemented in order to find out the existence of the long-run relationship among the BRICS indices. The statistics are calculated on the assumption of the existence of a linear trend. The results are summarized in Table 7. As we see from the table, both the Trace test and the Maximum Eigenvalue test fail to reject even the null hypothesis of "none" cointegrated equations at 5% level, meaning that the index series are not cointegrated and, thus, there is no long term relationship among them. Thus, the absence of cointegration implies that the VAR model should be used for further analysis.

Table 7. Johansen- Juselius Tests Results

Trace Test Results				
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**P-value**
None	0.33418	66.35132	69.81889	0.0916
At most 1	0.301908	42.3539	47.85613	0.1491
At most 2	0.17855	21.14908	29.79707	0.3484
At most 3	0.148119	9.54474	15.49471	0.3174
At most 4	0.001466	0.086542	3.841466	0.7686
Trace test indicates no cointegration at the 0.05 level.				

Maximum-Eigenvalue Test Results				
No. of CE(s)	**Eigenvalue**	**Statistic**	**Critical Value**	**P-value**
None	0.33418	23.99742	33.87687	0.4557
At most 1	0.301908	21.20482	27.58434	0.264
At most 2	0.17855	11.60434	21.13162	0.587
At most 3	0.148119	9.458198	14.2646	0.25
At most 4	0.001466	0.086542	3.841466	0.7686
Max-eigenvalue test indicates no cointegration at the 0.05 level.				

As the data series are I (1) the VAR model is estimated using the first differences. The results are presented in Appendix 1. As we see, DNIFTY (-2) is significant at 5% level to explain DIBOV, DJALSH and DRTS, DIBOV (-1) and DSHCOMP (-1) are significant to explain DNIFTY, DRTS (-1) and DSHCOMP (-1) are significant to explain DSHCOMP. The F-statistic of all the regressions is significant at 5% level, except when regressing DJALSH to the BRICS indices. R^2 is 31%-37% for almost all the models, again except when regressing DJALSH to the selected data series, for which the R^2 is 19%. Overall for all the models R^2 implies low forecasting power. In any case low R^2 values do not necessarily mean that the model is "bad" and other factors need to be considered for coming to a conclusion, especially the behavior of the residuals.

The residual tests are presented in Appendix 2. Based on the results of the residual tests, we fail to reject the null hypothesis of no autocorrelations, meaning that the residuals are not serially correlated. We also fail to reject the null hypothesis that residuals are multivariate normal, implying that residuals follow the normal distribution. But we reject the null of no heteroscedasticity at 5% significance level. The same model was run by using the log of the seasonally adjusted values. The residual tests are used for single models in VAR, and show that the models have both no serial correlation and no heteroscedasticity issue. By the way, the results of the log model do not differ significantly from the one analyzed in this paper. But, it is worth mentioning that using the logarithmic values means transforming the model, which may cause a low quality model to appear well-behaved. Thus, we can be confident that the results and conclusions made in this research are trustworthy and can be applied when making decisions.

The results of VAR Granger Causality/Block Exogeneity Wald Tests are summarized in Table 8. A Chi-square test statistic of 9.72 of DNIFTY with reference to DIBOV represents the hypothesis that lagged coefficients of DNIFTY are equal to zero. Similarly, the hypothesis of the lagged coefficients of other variables, as well as the block of "all" coefficients in the regression equation of DIBOV having zero values are tested. Summarizing the results, DNIFTY Granger causes DIBOV and DRTS at 5 % significance level, DIBOV and DSHCOMP Granger cause DNIFTY. Thus, there exists unidirectional causality from Indian stock market to Russian market and from Chinese stock market to Indian. As well as, we have bi-directional causal relationship between Indian and Brazilian stock markets. The null hypothesis of block exogeneity is rejected for all equations in the model, except for DSHCOMP and DJALSH, indicating that the mentioned indices are not jointly influenced by the other variables.

Table 8. VAR Granger Causality/Block Exogeneity Wald Tests

Dependent variable	Excluded	Chi-sq	df	Prob.
DIBOV	DRTS	1.469735	2	0.4796
	DNIFTY	9.716618	2	0.0078
	DSHCOMP	1.002876	2	0.6057
	DJALSH	2.012321	2	0.3656
	All	20.64351	8	0.0082
DRTS	DIBOV	2.330711	2	0.3118
	DNIFTY	16.37978	2	0.0003
	DSHCOMP	0.275584	2	0.8713
	DJALSH	0.300157	2	0.8606
	All	22.60481	8	0.0039
DNIFTY	DIBOV	6.5661	2	0.0375
	DRTS	2.651377	2	0.2656
	DSHCOMP	10.49016	2	0.0053
	DJALSH	1.932086	2	0.3806
	All	20.2889	8	0.0093
DSHCOMP	DIBOV	3.785239	2	0.1507
	DRTS	5.824764	2	0.0543
	DNIFTY	1.526837	2	0.4661
	DJALSH	0.991763	2	0.609
	All	11.66798	8	0.1666
DJALSH	DIBOV	2.789044	2	0.248
	DRTS	1.129377	2	0.5685
	DNIFTY	5.574183	2	0.0616
	DSHCOMP	2.347536	2	0.3092
	All	10.82138	8	0.212

Pairwise Granger causality tests results are illustrated in Table 9, and show that we can only reject the null hypothesis that DNIFTY does not Granger Cause DIBOV and DRTS, and that DSHCOMP does not Granger Cause DNIFTY. Thus, there is unidirectional short-term causal relationship that runs from Indian stock market to Brazilian and Russian markets, as well as from Chinese stock market to India, which complies with the Block Exogeneity Wald Tests results, except for the bi-directional causal relationship between Indian and Brazilian stock markets. So, as we saw from the correlation analysis most of the index series have high positive correlation, but only three of them have causal relationship with another.

Table 9. Pairwise Granger Causality Tests Results

Null Hypothesis:	Obs.	F-Statistic	Prob.
DRTS does not Granger Cause DIBOV	**59**	**0.60283**	**0.5509**
DIBOV does not Granger Cause DRTS		**0.45516**	**0.6368**
DNIFTY does not Granger Cause DIBOV	**59**	**7.02865**	**0.0019**
DIBOV does not Granger Cause DNIFTY		**1.329**	**0.2733**
DSHCOMP does not Granger Cause DIBOV	**59**	**2.38487**	**0.1017**
DIBOV does not Granger Cause DSHCOMP		**0.7576**	**0.4737**
DJALSH does not Granger Cause DIBOV	**59**	**1.18698**	**0.313**
DIBOV does not Granger Cause DJALSH		**0.94188**	**0.3962**
DNIFTY does not Granger Cause DRTS	**59**	**8.95499**	**0.0004**
DRTS does not Granger Cause DNIFTY		**0.49**	**0.6153**
DSHCOMP does not Granger Cause DRTS	**59**	**1.41245**	**0.2524**
DRTS does not Granger Cause DSHCOMP		**2.34279**	**0.1058**
DJALSH does not Granger Cause DRTS	**59**	**0.4861**	**0.6177**
DRTS does not Granger Cause DJALSH		**0.15637**	**0.8556**
DSHCOMP does not Granger Cause DNIFTY	**59**	**6.68913**	**0.0025**
DNIFTY does not Granger Cause DSHCOMP		**0.24624**	**0.7826**
DJALSH does not Granger Cause DNIFTY	**59**	**0.38068**	**0.6852**
DNIFTY does not Granger Cause DJALSH		**2.28441**	**0.1116**
DJALSH does not Granger Cause DSHCOMP	**59**	**0.46646**	**0.6297**
DSHCOMP does not Granger Cause DJALSH		**0.20967**	**0.8115**

Next the impulse response of each of the BRICS indices to a one-time shock to one of the innovations is analyzed. The results are presented in Figures 2 & 3, which show the impulse responses for 10 periods/quarters ahead. It is worth to mention here that the different ordering of the indices may result in different estimations for Cholesky decomposition of the innovation matrix.

Figure 2 presents the multiple graphs and plots the response to Cholesky one standard deviation innovations with ±2 standard deviations. The figure illustrates the impulse responses of each stock index to the corresponding market shock of BRICS markets 10 periods ahead. The solid lines plot the point estimates of the impulse responses of BRICS indices to one standard deviation shocks, and the dotted lines present the two standard deviation bands around the point estimates.

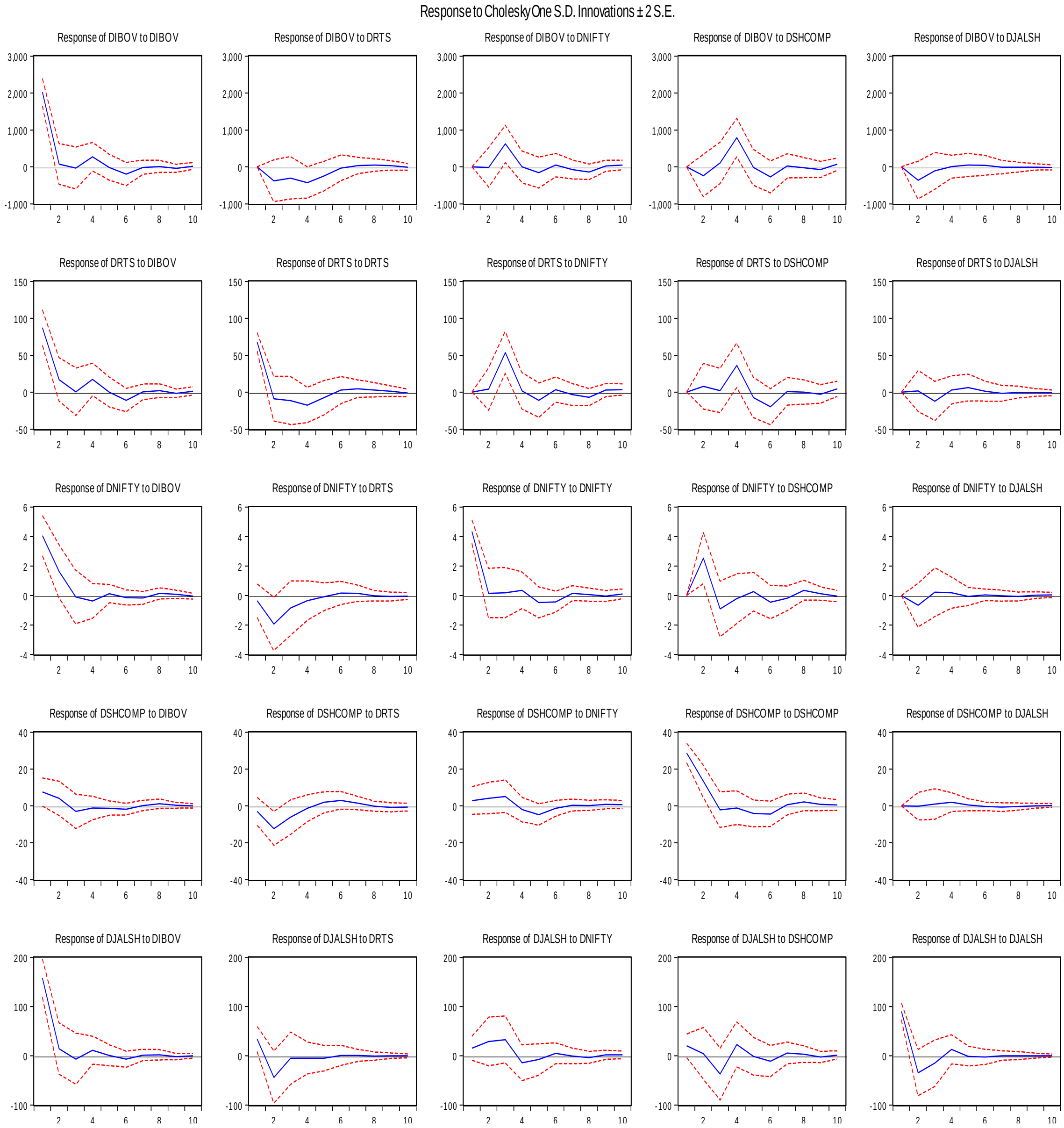


Figure 2. Response to Cholesky One S.D. Innovations with ± 2 standard deviations. The order of VAR is DIBOV, DRTS, DNIFTY, DSHCOMP, DJALSH, 10 periods ahead

Figure 3 presents the combined graph again for 10 periods ahead. It illustrates the responses of the BRICS indices to the shocks of other ones and the dynamic relations of the selected indices. The response of the Brazil stock market to positive one standard deviation shock to innovations is very high for the first period/quarter, then drops significantly to zero starting from the second period and fluctuates around it with slightly higher positive and negative responses for fourth and sixth quarters respectively. The response of the Russian stock market is high for the first quarter and drops below zero starting from the second period. Then it continues being negative until the sixth period. During and after the sixth quarter it is observed low positive response, which remains close to zero till the end of the 10th period. The response of the Indian stock market is similarly high and positive during the first quarter dropping close to zero starting from the second period. Low positive responses are observed for second, third, fourth and seventh periods, low negative responses for the fifth and sixth quarters and almost zero response till the 10th period. For the Chinese stock market, the response during the first quarter is again high and positive, steadily decreases during the second period and becomes negative starting from the third quarter. It remains negative till seventh period. During and after the seventh period low positive values are observed. Finally referring to the stock market of South Africa, the response is high and positive for the first quarter with some negative and positive values for the second and the fourth quarters respectively, and close to zero after on. It is worth mentioning that the magnitude of the response differs for the selected stock market indices. The dynamic linkages of BRICS indices are visually illustrated in Figure 3. For stationary VARs, the impulse responses should die out to zero as time passes, which is seen both in Figure 2 and 3.

The impulse response functions evaluate the impact of a shock on the returns of one stock market to the returns of other stock markets in the VAR model, whereas the variance decomposition separately estimates the variation in the returns of one stock market into the component shocks to the VAR, showing the relative importance of each random innovation in affecting the stock market returns. The results of the variance decomposition are summarized in Table 10. The S.E. column shows the forecast error, which is the result of the variation in the current and future values of the innovations to each stock market returns in the VAR model. The rest of the columns indicates the percentage of the forecast variance due to each innovation, which implies that the sum of each row is 100%. Here, again the variance decomposition can change significantly in case of changing the order of variables. The ordering of the variables if the following: DIBOV, DRTS, DNIFTY, DSHCOMP, DJALSH. DIBOV is ordered first in the Cholesky decomposition. After 10 periods, about 30% in the innovations originated in the stock market of Brazil are affected by the stock markets from other countries of BRICS compared to the 0% for the first quarter. From the mentioned 30%, 13% is due to the Chinese stock market, 8% and 7% due to Russian and Indian stock markets. Russian stock market explains about 28% of its own innovation after 10 quarters compared to the 38% for the first period. The highest impact relates to the Brazilian stock market 45%, as well as 17% and 10% to Indian and Chinese stock markets correspondingly. Referring to the Indian stock market, it is observed 37% influence from both its own and Brazilian stock markets for 10 periods ahead, as well as 15% and 9% from Chinese and Russian stock markets. The Chinese stock markets are explained by 73% by their own market after 10 quarters compared to current 92%. As we see Indian and Russian stock markets have increased their influence on Chinese index from 1% to nearly 6% and 15% respectively. The South African stock market is affected by its own market 22-23%, which does not change significantly for the future 10 periods. It is highly impacted by the Brazilian market nearly 60%. To summarize, only Brazilian and Chinese stock markets are highly affected by their own markets, as well as Russian, Indian and South African markets are highly impacted by the Brazilian stock markets for 10 periods ahead.

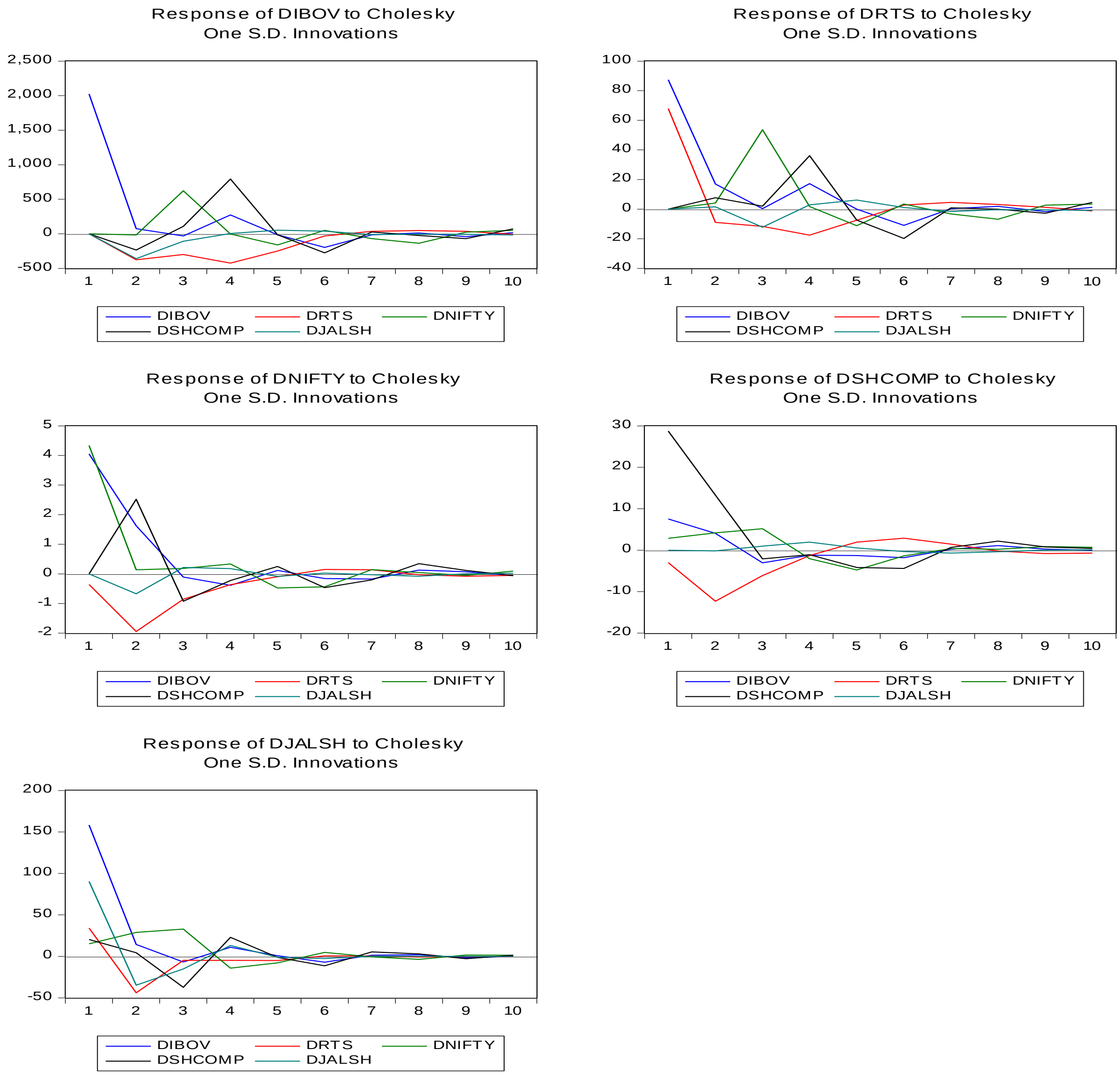


Figure 3. Combined figure. The order of VAR is DIBOV, DRTS, DNIFTY, DSHCOMP, DJALSH, 10 periods ahead

7. Conclusion

According to the theoretical framework of the research – CAPM and the EMH theory, in the efficient markets, international investors are rewarded per systematic risk taken through diversifying the unsystematic or the idiosyncratic risk of separate countries. In general, international portfolio diversification helps investors to reduce the unsystematic risk, as financial assets happen to be less correlated across the countries than within a country. But taking into account the current trends of globalization, as well as the relaxation of the capital flow among the countries, the increasing trend of the financial integration of the global stock markets is an issue of keen financial interest.

As the markets of the developed countries, especially the US and the EU, have experienced economic and financial crisis during the recent decades, the international investors have turned to the emerging markets in search for new investment avenues. And as the BRICS markets compose nearly two-thirds of the emerging markets, most of them are the largest and most integrated economies in their respective regions, and thus, have significant influence in the world economic dynamics, the existence and the level of financial integration among those countries is of an essential interest among the investors, governments, as well as the researchers.

Table 10. Variance Decomposition Results. Cholesky Ordering: DIBOV DRTS DNIFTY DSHCOMP DJALSH

Variance Decomposition of DIBOV:						
Period	**S.E.**	**DIBOV**	**DRTS**	**DNIFTY**	**DSHCOMP**	**DJALSH**
1	2025.502	100	0	0	0	0
2	2106.132	92.61618	3.214472	0.006673	1.249305	2.913368
3	2221.948	83.23425	4.720612	7.830972	1.36079	2.853376
4	2412.831	71.86444	7.111512	6.641014	11.96293	2.420104
5	2431.706	70.75648	8.061386	6.973765	11.78133	2.427047
6	2456.137	69.9967	7.917132	6.875976	12.80822	2.401975
7	2457.604	69.91634	7.928665	6.95044	12.8033	2.401254
8	2461.968	69.67087	7.936648	7.230957	12.76836	2.393163
9	2463.676	69.60169	7.945882	7.230221	12.83163	2.390575
10	2465.335	69.51303	7.936314	7.261505	12.89692	2.392234
Variance Decomposition of DRTS:						
Period	**S.E.**	**DIBOV**	**DRTS**	**DNIFTY**	**DSHCOMP**	**DJALSH**
1	110.7527	62.28899	37.71101	0	0	0
2	112.7543	62.36328	37.01071	0.135151	0.471167	0.019698
3	126.02	49.92555	30.47983	18.2285	0.403224	0.962895
4	133.4201	46.20778	28.92234	16.27989	7.684243	0.905745
5	134.4522	45.50112	28.79555	16.73114	7.869336	1.102847
6	136.4301	44.84175	28.0067	16.31195	9.761594	1.078007
7	136.5562	44.75949	28.06445	16.33947	9.747844	1.088749
8	136.7765	44.63507	28.02394	16.53877	9.716464	1.085758
9	136.8482	44.60319	28.00298	16.56009	9.748049	1.085682
10	136.9822	44.52426	27.9559	16.59206	9.839984	1.087802
Variance Decomposition of DNIFTY:						
Period	**S.E.**	**DIBOV**	**DRTS**	**DNIFTY**	**DSHCOMP**	**DJALSH**
1	5.945541	46.472	0.35905	53.16895	0	0
2	6.973525	39.23094	8.075341	38.68834	13.08204	0.923341
3	7.093538	37.93705	9.271567	37.45633	14.34725	0.987795
4	7.127044	37.87434	9.446188	37.32418	14.31386	1.041434
5	7.149476	37.66341	9.404574	37.53845	14.34538	1.048181
6	7.181144	37.37931	9.364839	37.57915	14.63617	1.040534
7	7.188974	37.35715	9.382051	37.53628	14.68438	1.040144
8	7.198899	37.28598	9.357752	37.43634	14.87114	1.048794
9	7.200798	37.27615	9.364945	37.42218	14.88838	1.048339
10	7.202074	37.26895	9.366849	37.42551	14.8897	1.049
Variance Decomposition of DSHCOMP:						
Period	**S.E.**	**DIBOV**	**DRTS**	**DNIFTY**	**DSHCOMP**	**DJALSH**
1	30.01426	6.271879	1.000851	0.90001	91.82726	0
2	35.53386	5.781616	12.70563	2.030444	79.47986	0.002451
3	36.62763	6.132463	14.74202	3.920067	75.13299	0.072456
4	36.79531	6.187417	14.73302	4.1948	74.53509	0.349669
5	37.41261	6.100349	14.51724	5.676579	73.34579	0.360036
6	37.85438	6.186348	14.77478	5.67786	73.00143	0.359573
7	37.89776	6.175929	14.89296	5.674322	72.86422	0.392571
8	37.98057	6.235803	14.83158	5.653568	72.8784	0.400648
9	38.00815	6.231906	14.8566	5.695665	72.81563	0.400198
10	38.02433	6.226606	14.87876	5.726291	72.76743	0.400908
Variance Decomposition of DJALSH:						
Period	**S.E.**	**DIBOV**	**DRTS**	**DNIFTY**	**DSHCOMP**	**DJALSH**
1	187.2712	71.57268	3.309204	0.656323	1.174661	23.28713
2	198.1616	64.44975	7.863449	2.727617	1.095883	23.8633
3	205.0588	60.29534	7.399385	5.133204	4.345069	22.827
4	207.5821	59.11871	7.276407	5.482399	5.449725	22.67276
5	207.7991	58.99686	7.320667	5.612582	5.441889	22.628
6	208.3053	58.82539	7.28582	5.637534	5.717618	22.53364
7	208.382	58.7867	7.280974	5.634261	5.780926	22.51714
8	208.4441	58.75999	7.278579	5.660474	5.797199	22.50375
9	208.4767	58.74872	7.276512	5.664277	5.813764	22.49672
10	208.4871	58.74288	7.276175	5.668549	5.817839	22.49456

Thus, this study has analyzed the short-run interlinkages and the long-run cointegration level among the BRICS stock markets. The ADF and PP are applied for evaluating the level of stationarity of the data. The results indicate that the series are integrated of order one – I (1). Thus, Johansen and Juselius cointegration tests are employed. The results showed no cointegration, meaning that no long-run relationship is observed among the BRICS indices. Correlation test results found high positive linkages between the stock markets, but unidirectional granger causality is observed only from Indian stock market to Brazilian and Russian markets, as well as from Chinese stock market to Indian stock market. The results of VAR Granger Causality/Block Exogeneity Wald Tests are in mostly in compliance with the aforementioned Pairwise Granger causality test results, except for the existence of bi-directional causal relationship between Indian and Brazilian stock markets.

The impulse response analysis illustrates that almost all stock markets have demonstrated similar behavior to the one standard deviation shock to innovations with high responses for the first period, which die out to zero as time passes. It is worth to mention that they differ significantly by the magnitude of the response.

The Variance Decomposition Analysis test results assessed the role of each of the BRICS markets on each other's movement. Thus, Brazilian and Chinese stock markets are highly affected by their own markets, as well as Russian, Indian and South African markets are highly impacted by the Brazilian stock markets for 10 quarters ahead.

Summarizing the results of the analysis, we may conclude that the Chinese stock markets are the most independent among the BRICS countries, and, thus, may provide diversification benefits to the international investors both for the short and the long run, and all the BRICS markets can provide gains for the investors in the long run as a result of being not cointegrated. Thus, all the BRICS countries can be seen as favorable destination for long-term international investments, with the Chinese market having the dominance for the short and long terms. It is worth to restress here, that China is the largest country among the emerging markets and is twice the size of the other BRICS markets combined.

This research is relevant for the policy makers in responding to increasing financial interactions across borders. The value of this research for the government agencies is that the economic dynamics and political changes of China followed by India must be reacted on the short-term period when dealing with policy responses regarding the other BRICS countries in special, and thus, the emerging countries in general.

The finding of the three comparative studies, discussed in the Literature Review, mostly contradict with the findings of this research, except for the analysis done by Sharma *et al.* (2013), who have found that BRICS stock markets are not closely interlinked implying diversification opportunities for the investors, which is in compliance with our research. The research also found that there are domestic factors that influence the stock markets. Naidu *et al.* (2014) have concluded that BRICS countries exhibit integration among the financial markets as group, which lowers the benefits from international diversification, but the same is not true for in country to country financial integration. The unique finding of the study is that Indian and Chinese stock markets are negatively correlated, which shows their independent states. It is worth to mention here that the study applies the BSE Sensex index of India as opposed to our NIFTY. Nashier (2015) have found evidence for short-term, as well as for long-term integration among the BRICS stock market indices, implying limited benefits for diversification. The findings of the mentioned last two studies contradict with our results, but, as it is mentioned in the literature review, the analysis do not capture the recent data, are limited through using the causality and/or cointegration tests, apply local value, transformed and/or high frequency data, etc. Going further, the domestic macro-economic factors of BRICS countries must also be considered for making decisions, which can and do have an impact on the stock market indices. This can be addressed in the future studies.

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Appendix 1. VAR Model Output

	DIBOV	DRTS	DNIFTY	DSHCOMP	DJALSH
DIBOV(-1)	0.501884	0.009993	0.001945	0.005834	0.037061
	-0.26189	-0.01432	-0.00077	-0.00388	-0.02421
	[1.91638]	[0.69784]	[2.53061]	[1.50332]	[1.53058]
DIBOV(-2)	-0.16746	-0.02141	-0.00061	-0.00578	-0.0221
	-0.27109	-0.01482	-0.0008	-0.00402	-0.02506
	[-0.61773]	[-1.44430]	[-0.76345]	[-1.43894]	[-0.88190]
DRTS(-1)	-3.72632	-0.12487	-0.02086	-0.156	-0.39401
	-4.36754	-0.23881	-0.01282	-0.06472	-0.40381
	[-0.85318]	[-0.52289]	[-1.62725]	[-2.41045]	[-0.97573]
DRTS(-2)	-3.58384	0.054878	0.001102	-0.00477	0.172086
	-4.2393	-0.2318	-0.01244	-0.06282	-0.39195
	[-0.84539]	[0.23674]	[0.08859]	[-0.07585]	[0.43905]
DNIFTY(-1)	13.48416	0.726236	-0.00311	0.668433	7.756579
	-63.9714	-3.4979	-0.18778	-0.94794	-5.91459
	[0.21078]	[0.20762]	[-0.01655]	[0.70514]	[1.31143]
DNIFTY(-2)	174.9467	12.3901	0.040135	0.955204	11.47455
	-56.6666	-3.09848	-0.16634	-0.8397	-5.2392
	[3.08730]	[3.99877]	[0.24129]	[1.13756]	[2.19013]
DSHCOMP(-1)	-5.3776	0.256738	0.092928	0.463056	0.419955
	-10.0892	-0.55167	-0.02962	-0.1495	-0.93281
	[-0.53301]	[0.46538]	[3.13784]	[3.09729]	[0.45020]
DSHCOMP(-2)	11.17722	0.058535	-0.05772	-0.28493	-1.6351
	-11.5426	-0.63114	-0.03388	-0.17104	-1.06719
	[0.96834]	[0.09274]	[-1.70352]	[-1.66584]	[-1.53215]
DJALSH(-1)	-3.97791	0.017511	-0.00742	-0.00195	-0.38392
	-2.80421	-0.15333	-0.00823	-0.04155	-0.25927
	[-1.41855]	[0.11421]	[-0.90081]	[-0.04684]	[-1.48077]
DJALSH(-2)	-0.5699	-0.08117	0.00784	0.041784	-0.10179
	-2.87908	-0.15743	-0.00845	-0.04266	-0.26619
	[-0.19795]	[-0.51558]	[0.92768]	[0.97941]	[-0.38238]
C	64.64894	-3.24674	0.928913	2.001856	34.27251
	-285.63	-15.618	-0.83842	-4.23252	-26.4084
	[0.22634]	[-0.20788]	[1.10793]	[0.47297]	[1.29779]
R-squared	0.310459	0.333814	0.316447	0.371345	0.193576
Adj. R-squared	0.166804	0.195025	0.17404	0.240375	0.025571
Sum sq. resids	1.97E+08	588776	1696.774	43241.09	1683383
S.E. equation	2025.502	110.7527	5.945541	30.01426	187.2712
F-statistic	2.16115	2.405194	2.222135	2.83535	1.152203
Log likelihood	-526.831	-355.361	-182.806	-278.329	-386.351
Akaike AIC	18.23157	12.41902	6.569705	9.807767	13.46954
Schwarz SC	18.61891	12.80636	6.957043	10.1951	13.85687
Mean dependent	85.04462	7.848223	1.1012	4.792176	32.98595
S.D. dependent	2219.01	123.4421	6.542022	34.43723	189.7124

Appendix 2. Residual Analysis

Table 2.1. VAR Residual Portmanteau Tests for Autocorrelations

Null Hypothesis: no residual autocorrelations up to lag h
Sample: 2000Q1 2015Q2
Included observations: 59

Lags	Q-Stat	Prob.	Adj Q-Stat	Prob.	df
1	6.120402	NA*	6.225926	NA*	NA*
2	11.76201	NA*	12.06549	NA*	NA*
3	43.93284	0.5171	45.95975	0.4322	45
4	66.69219	0.59	70.37433	0.465	70
5	88.48416	0.6683	94.18407	0.5044	95
6	120.1231	0.4797	129.4048	0.2628	120
7	150.4454	0.3613	163.8089	0.1359	145
8	171.7053	0.449	188.4037	0.1586	170
9	187.9277	0.6288	207.5461	0.256	195
10	206.5214	0.7338	229.9345	0.3091	220
11	221.6717	0.8552	248.5567	0.4247	245
12	246.2611	0.8471	279.4243	0.3338	270

Table 2.2. VAR Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: residuals are multivariate normal
Sample: 2000Q1 2015Q2
Included observations: 59

Component	Skewness	Chi-sq	df	Prob.
1	-0.384294	1.452208	1	0.2282
2	-0.608604	3.642253	1	0.0563
3	-0.088263	0.076605	1	0.782
4	0.279752	0.769568	1	0.3804
5	-0.469741	2.169791	1	0.1407
Joint		8.110425	5	0.1503

Component	Kurtosis	Chi-sq	df	Prob.
1	3.815123	1.633381	1	0.2012
2	3.195024	0.093501	1	0.7598
3	2.730076	0.179112	1	0.6721
4	3.851454	1.782228	1	0.1819
5	3.538007	0.711567	1	0.3989
Joint		4.399789	5	0.4934

Component	Jarque-Bera	df	Prob.
1	3.085589	2	0.2138
2	3.735754	2	0.1545
3	0.255716	2	0.88
4	2.551797	2	0.2792
5	2.881359	2	0.2368
Joint	12.51021	10	0.2524

Table 2.3. VAR Residual Heteroscedasticity Tests

Joint test		
Sample: 2000Q1 2015Q2		
Included observations: 59		
Chi-sq	**df**	**Prob.**
357.8456	300	0.0122

Individual components:

Dependent	R-squared	F(20,38)	Prob.	Chi-sq(20)	Prob.
res1*res1	0.421578	1.3848	0.1898	24.87311	0.2063
res2*res2	0.447535	1.539135	0.124	26.40459	0.1529
res3*res3	0.596991	2.814536	0.003	35.22248	0.019
res4*res4	0.56671	2.485051	0.0077	33.43588	0.0302
res5*res5	0.418962	1.370011	0.1974	24.71877	0.2124
res2*res1	0.395856	1.244944	0.2735	23.35548	0.2717
res3*res1	0.556225	2.381449	0.0105	32.81728	0.0353
res3*res2	0.5776	2.59811	0.0055	34.07842	0.0256
res4*res1	0.551001	2.331634	0.0121	32.50905	0.0382
res4*res2	0.5097	1.975176	0.0349	30.07229	0.0687
res4*res3	0.629153	3.223404	0.0009	37.12001	0.0113
res5*res1	0.442854	1.510238	0.1345	26.1284	0.1616
res5*res2	0.442297	1.50683	0.1357	26.09551	0.1627
res5*res3	0.546033	2.285322	0.0139	32.21592	0.0411
res5*res4	0.567554	2.493614	0.0075	33.4857	0.0298